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FORECASTING BANK STOCK MARKET PRICES WITH A HYBRID METHOD: THE CASE OF ALPHA BANK

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Abstract. The present study aims at constructing Confidence Intervals (C.I) for the predicted values of a Time Series with the application of a Hybrid method. The presented methodology is complicated and thus is completed in different stages. Initially the Artificial Neural Networks (ANNs) is applied on the raw time series in order to estimate C.I of the forecasts. Then, the Bootstrap method is employed on the residuals generated by the preceded process. On the upper and lower limit of the estimated C.I., two new ANNs are employed in order to make point estimations (of the upper and lower limits) using of Object Oriented Programming. For the empirical analysis daily observations of the closing prices of Alpha Bank stocks have been used. The sample period is extended from 28/01/2004 until 30/11/2005. The nonstationarity of the time series employed in our study is not a forbidding condition for the estimation of the confidence intervals, in our case, since the level of bootstrap still provides a satisfactory approximation for the roots arbitrarily close to unity (Berkowitz, Kilian 1996). The accuracy of the forecasts was surveyed with the use of different criteria and the results were satisfactory.

Keywords: Artificial Neural Networks, Confidence interval, Bootstrap method, Visual Programming, Stock Markets, Time Series.

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JEL Classification: C15, C88, G17.

1. Introduction

Forecasting in Finance and Economics has been a subject of extended study within the last decade (McAdam, McNellis 2005). In most cases the forecasts are based on time series modeling (Borovkova *et al*. 2003). Forecasting can also be based on the application of different methods like, bootstrapping (De Peretti 2003; Hatemi, Roca 2006) and Artificial Neural Networks (Kiani, Kastens 2008). The combined use of Bootstrap methods and Artificial Neural Networks (ANNs) has also been used in Forecasting in the past (Focarelli 2005). In our study we present a different method which relies on the application of ANNs for the estimation of the (1-α)*100%(C.I) of the predicted values of the estimated time series. The estimation of this time series is based on the application of the Bootstrap method on the residuals.

In detail we apply a hybrid method that includes the combined application of ANNs on the Upper Confidence Limit (UCL) and Lower Confidence Limit (LCL) of the (1-α)*100% (C.I), that have been a result of the Bootstrap method on the residuals**,** aiming at the prediction of the confidence intervals.

The paper is organised as follows, section 1 introduces the subject of the study, section 2 is a review of the literature, and section 3 describes the methodology used to generate predictions. The empirical results are given in section 4, and finally section 5 provides some concluding remarks.

2. Literature review

Claeskens and Keilgom (2003), construct bootstrap confidence bands for regression curves. Kolsrud (2007) proposes principles and methods for the construction of a time-simultaneous prediction band for a univariate time series. The methods are entirely based on a learning sample of time trajectories, and make no parametric assumption about its distribution. The expected coverage probability of a band can be estimated with a bootstrap procedure. In Kim (2002), the construction of bootstrap prediction intervals is based on the percentile and percentile-*t* methods, employing the standard bootstrap as well as the bootstrap-after-bootstrap method.

The use of GARCH models in modelling the stock prices; behavior is used greatly within the last years (Teresienė 2009; Aktan *et al*. 2010). Tambakis and Van Royen (2002), on the other hand, used the bootstrap methodology to estimate the data's conditional predictability using GARCH models. This result is then compared to predictability under a random walk and a model using the prediction bias in uncovered interest parity (UIP). Mark (1995) suggested bootstrapping in testing the null hypothesis of no predictability. Based on the bootstrap tests, the author found strong evidence favouring the forecast accuracy of the monetary model relative to the random walk. Thombs and Schuchany (1990) have developed a method of calculating bootstrap conditional prediction intervals for autoregressive models.

McCullough, (1994), applies the bootstrap method in estimating forecast intervals for an AR(p) model. Ankenbrand and Tomassini (1996), present an integrated approach for modelling the behaviour of financial markets with ANNs. Fernando Fernández-Rodríguez *et al.* (2000), investigate the profitability of a simple technical trading rule based on ANNs. Ioannou *et al.* (2009), used ANNs in order to predict the future prices of fuelwood. It is obvious that within the last decade, there has been an increasing interest in surveying the predictable components in stock prices (Fama 1991). Patterns in asset prices improved stock-market forecast ability with different techniques (Fernandez-Rondriquez *et al.* 1997). One of the approaches that improved the ability of forecasting security markets is the ANNs (Van Eyden 1995; Gencay, Stengos 1998a). Brock *et al.* (1992) used bootstrap simulations of various null asset pricing models and found that simple technical trading rule profits cannot be explained by popular statistical models of stock index returns. Dogan (2007) proposed the bootstrapping method for confidence interval estimation and hypothesis testing in system dynamics models and provided an overview of the issues related to the proper application of bootstrapping in dynamic models.

Gencay and Stengos (1998b, 1999), confirm predictive power of simple technical trading rules in forecasting the current returns using feed forward network and NN regressions, while Gencay and Stengos (1997), and Gencay and Stengos (1998c), find evidence of nonlinear predictability in stock market returns by using the past buy and sell signals of the moving average rules. Regarding foreign exchange markets, Le Baron (1992) and Le Baron (1998), use the bootstrap methodology to demonstrate the statistical significance of the technical trading rules against several parametric null models of exchange rates. Furthermore, Le Baron (1999) and Sosvilla-Rivero *et al.* (1999), discover that excess returns from extrapolative technical trading rules in foreign exchange markets are high during periods of central bank intervention. Gencay (1999), by using feed forward network and NN regressions, finds statistically significant forecast improvements for the current returns over the random walk model of foreign exchange returns.

Skabar and Cloete (2002), describe a methodology in which neural networks can be used indirectly, through a genetic algorithm based on weight optimisation procedure, in order to determine buy and sell points for financial commodities traded on a stock exchange. A number of studies applied the simulation of trading agents based on ANNs (White 1988; Kimoto *et al*. 1990; Weigend and Gershenfeld 1994). The traditional approach to supervise neural network weight optimisation is the well-known back propagation algorithm (Rumelhart, McClelland 1986), while Beltratti and Terna (1996), suggest the use of genetic search for neural network weight optimisation in this field.

Ruiz and Pascual (2002), review the application of bootstrap procedures in inference and prediction of financial time series. However, bootstrap methods are not adequate in this context. Korajczyk (1985) presents one of the earliest applications of bootstrap methods to analyze financial problems. Given that the basic bootstrap techniques were originally developed for independent observations, the bootstrap inference has not the desired properties when applied to raw returns; Bookstaber and McDonald (1987), Chatterjee and Pari (1990), Hsie and Miller (1990) and Levich and Thomas (1993) present the problems of surveys where returns are directly bootstrapped. Maddala and Li (1996) pointed out the shortcomings in the application of bootstrap methods in finance. On the other hand, Thombs and Schucany (1990), as well as Kim (2002), argue that bootstrap-based methods can also be used to obtain prediction densities and intervals for future values of a given variable without making distributional assumptions on the innovations and, at the same time, allowing the introduction, into the estimated prediction densities, of the variability due to parameter estimation. Mizuno *et al.* (1998), employ ANN to Tokyo stock exchange to predict buying and selling signals with an overall prediction rate of 63%. Sexton *et al.* (1998) concluded that the use of momentum and start of learning at random points may solve the problems that may occur in training processes. Phua *et al.* (2000), applied neural networks with genetic algorithms to the stock exchange market of Singapore and predicted the market direction with an accuracy of 81%. In Turkey, ANNs are mostly used in predicting financial failures (Yildiz 2001). There is no empirical survey concerning the prediction of Turkish stock market values with exception that of Birgul Egeli *et al.* (2003), who use artificial neural networks to predict Istanbul Stock Exchange (ISE) market index value. To be more specific, the aim of their study was to use ANNs in order to forecast Istanbul Stock Exchange (ISE) market index values.

What must also be mentioned is the greater predictability performance of ANN compared to that of other conventional models like autoregressive models, as provided by the current literature. Evidently, according to Al Saba and El Amin (1998), F-M Tseng *et al.* (2002), Gutierrez-Estrada *et al*. (2003), Koutroumanis *et al.* (2009), Prybutok *et al.* (2000), Artificial Neural Networks tend to perform better and predict better results when compared to Auto Regressive Moving Average (ARIMA) models.
Le Baron and Weigend (1997) by using a bootstrap or resampling method, compare the uncertainty in the solution stemming from the data splitting with neural network specific uncertainties (parameter initialization, choice of number of hidden units, etc.).

Parisi *et al.* (2008), analyze recursive and rolling neural network models to forecast one-step-ahead sign variations in gold price. Different combinations of techniques and sample sizes are studied for feed forward and ward neural networks. White and Racine (2001) suggest tests for individual and joint irrelevance of network inputs. Tests of this type can be used to determine whether an input or group of inputs belong and quote in a particular model permitting valid statistical inference to be based on estimated feed forward neural network models. The approaches employ well known statistical resampling techniques. Lento and Gradojevic (2007) determine the profitability of technical trading rules by evaluating their ability to outperform the naïve buy-and-hold trading strategy. The bootstrap methodology is used to determine the statistical significance of the results.

3. Artificial neural networks

A neural network consists of a number of elements called neurons. Each neuron receives a number of signals which come as an input to it. The neuron has some possible states on which his internal structure may be, that receives the input signals and finally has only one output which is a function of input signals. Each signal transmitted from one neuron to another through the neural network is coupled with a weight value, w, which indicates how closely these two neurons are connected with this weight. This value fluctuates on a specific interval, for example, the interval between –1 and 1, although this interval is an arbitrary choice and is dependent on the problem we want to solve. The meaning of the weight value is to show us the importance of the contribution of the specified signal to the configuration of the structure of the network for the two neurons that connects. When w is big then the contribution of the signal is also big.

The primary aim of an Artificial Neural Network is to solve specific problems that we present to it, or to perform certain tasks (like image recognition). In order to solve or perform these tasks the network must be trained. This is exactly the main characteristic of neural networks meaning that they learn by training. By using the word “training” in neural networks we mean that we provide some input and we get some outputs. Inputs are in essence, the presentation to the network of some signals taking arithmetic values, i.e. a binary number consisting of 0 and 1. These numbers given at the input of the network constitute a prototype. There is a possibility that for a given problem many prototypes are required. To each prototype corresponds a correct answer, which is the signal we must receive at the output or else the objective.

When the network stops changing weight values, we assume that training is complete. This happens because the error at the input is nearly or equal to zero. Typically the architecture of an ANN consists of the Input Layer where we provide the data, the Hidden Layer where data are being processed and may consist of various levels and finally the Output layer from where we read the results of the network (Argyrakis 2001).

4. Bootstrap method

Bootstrapping is the practice of estimating properties of an estimator (such as its variance) by measuring those properties when sampling from an approximating distribution. One standard choice for an approximating distribution is the empirical distribution of the observed data. In the case where a set of observations can be assumed to be from an independent and identically distributed population, this can be implemented by constructing a number of resamples of the observed dataset (and of equal size to the observed dataset), each of which is obtained by random sampling with replacement from the original dataset.

It may also be used for constructing hypothesis tests. It is often used as an alternative to inference based on parametric assumptions when those assumptions are in doubt, or where parametric inference is impossible or requires very complicated formulas for the calculation of standard errors (Fig. 1).

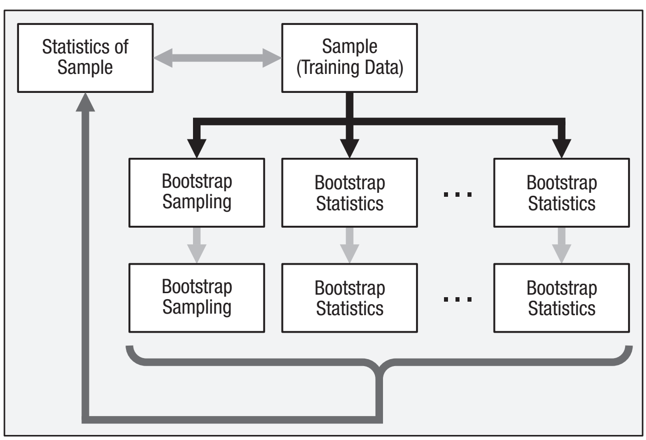

Fig. 1. Bootstrap Methodology

The idea of bootstrap is depicted in the diagram above. Suppose that the researcher wants to assess statistical accuracy of the sample data (statistics of sample), he can take N bootstrap samplings and compute the statistics from each bootstrap sampling. The values of bootstrap statistics are used to evaluate the statistical accuracy of the original sample statistics (Teknomo 2006).

The advantage of bootstrapping against other analytical methods is its great simplicity – it is straightforward to apply the bootstrap to derive estimates of standard errors and confidence intervals for complex estimators of complex parameters of the distribution, such as percentile points, proportions, odds ratio, and correlation coefficients (Efron 1982).

5. Hybrid method

In this study we propose a hybrid methodology that may allow us to make forecasts on the confidence intervals of the predicted values of a time series. This method includes ANNs and Bootstrap methods. Those two methodologies can be combined by the use of Excel and Visual Basic for Applications. This application is implemented in the following steps:

1st Step: ANN is applied in order to estimate the real values of the time series and to make forecasts on its future values.

2nd Step: Initially, the residuals are estimated. The Bootstrap method is applied on the new residuals. The application of Breusch Godfrey LM test as well as ARCH and Breusch Pagan test did not trace any problem of autocorrelation and heteroskedasticity. This result implies that the bootstrap sample of the residuals $\boldsymbol{e}^*$ of size N, can be considered as random independent and identically distributed sample drawn with replacement from the empirical distribution function (EDF) of the residuals. Furthermore, Bootstrap based methods can also be used to obtain prediction densities and intervals for future values of a given variable without making distributional assumptions on the innovations and, at the same time, allowing the introduction, into the estimated prediction densities, of the variability due to parameter estimation (Kim 2001; Thombs, Schucany 1990).

The sample $\boldsymbol{e}^*$ can be considered a randomly resampled version of e residuals: its elements are the same as those of the original data set but some may appear once, some two or more times and some others may not appear at all. Supposing B is independent bootstrap time series of the residuals $\boldsymbol{e}^{*1}$, $\boldsymbol{e}^{*2}$, ………, $\boldsymbol{e}^{*B}$. Each time series consists of N data values generated with replacement from $\boldsymbol{e}$ (Mooney, Duval 1993). This means that for every real value of the time series we take B+1 residuals randomly distributed.

3rd step: For every residual B new bootstraping residuals are calculated. Within this process the (1-α)*100% (Bootstrap C.I.) of each residual is estimated, a process that is repeated for all B+1 residuals. Based on the B.C.I, we estimate the C.I. of the predictions. The technique of bootstrapping applied on the residuals has been extensively used in the past (Shao, Tu 1955; Efron, Tibshirani 1986; Hall 1986, 1988; Beran 1988; Franklin, Wasserman 1992; Simar, Wilson 1998; Glaz, Sison 1999; Bjørnstad, Falck 2001; Tribouley 2004; Chou 2006; Pesavento, Rossi 2006; Kapetanios 2008; Xiong, Li 2008; Charitos *et al.* 2009; Jun Li *et al.* 2009; Annaert *et al*. 2009; Kascha, Mertens 2009; Barnes *et al.* 2009).

4th step: Based on the process mentioned above two new time series of the upper and lower limits of the B.C.I. are generated. In the fourth step with the application of ANN on the upper and lower limit of BCI, we can make forecasts about the upper and lower limits of the C.I. of the predicted value respectively. Consequently, we can estimate the C.I. of the predicted values regarding the initial time series.

6. Application of the hybrid method – results

This methodology is applied to a time series of the stock prices of Alpha Bank for the time period from 28/01/2004 till 30/11/2005 (daily prices) that the initial ANN is used. In order to implement an accuracy test for the forecasts we used the last twenty observations of our time series, with the assistance of statistical tests. For the evaluation of forecasting accuracy the following statistical tests were used; RMSE, MAPE, NOF and Theil' – U Statistic. An A.N.N is created using as input the real values of the stock price of Alpha bank for the same time period (28/01/2004 till 30/11/2005) through which we estimate the forecasted values of the Alpha Bank stock prices. Then the residuals are estimated with the application of ANN. In order to train the neural network we used the Kalman filter which consists of one input neurons, 24 hidden neurons and 1 output neuron. During the ANN development, we created several other ANN's with different numbers of neurons. The network described here, provided the best results. The application we used (Neural Ware Predict) automatically uses a part of the time series for training, testing and validation, thus protecting the network from overfitting. Kalman filters are based on linear dynamical systems discretised in the time domain. They are modelled on a Markov chain built on linear operators perturbed by Gaussian noise. The state of the system is represented as a vector of real numbers. At each discrete time increment, a linear operator is applied to the state to generate the new state, with some noise mixed in, and optionally some information from the controls on the system if they are known. Then, another linear operator mixed with more noise generates the visible outputs from the hidden state. The Kalman filter may be regarded as analogous to the hidden Markov model, with the key difference that the hidden state variables are continuous (as opposed to being discrete in the hidden Markov model). Additionally, the hidden Markov model can represent an arbitrary distribution for the next value of the state variables, in contrast to the Gaussian noise model that is used for the Kalman filter (Haikin 2001). In our case, we used the Kalman filter in order to train the network which consists of two input neurons, 24 hidden neurons and 1 output neuron.

Kalman filters are based on linear dynamic systems. They are modelled on a Markov chain built on linear operators perturbed by Gaussian noise. The state of the system is represented as a vector of real numbers. At each discrete time increment, a linear operator is applied to the state to generate the new state, with some noise mixed in, and optionally, some information from the controls on the system, if they are known. Then, another linear operator mixed with more noise generates the visible outputs from the hidden state. The Kalman filter may be regarded similar to the hidden Markov model, with the key difference that the hidden state variables are continuous (as opposed to being discrete in the hidden Markov model). Additionally, the hidden Markov model can represent an arbitrary distribution for the next value of the state variables, in contrast to the Gaussian noise model that is used for the Kalman filter. There is a strong duality between the equations of the Kalman Filter and those of the hidden Markov model. The Kalman filter model assumes the true state at time k has evolved from the state at (k − 1) according to:

$$x_k = F_k x_{k-1} + B_k u_k + w_k \, , \tag{1}$$

where: F_k is the state transition model which is applied to the previous state x_{k-1}; B_k is the control-input model which is applied to the control vector uk; w_k is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q_k.

$$w_k \sim N(0, Q_k) \, . \tag{2}$$

At time k an observation (or measurement) z_k of the true state x_k is made according to:

$$z_k = H_k x_k + v_k \, , \tag{3}$$

where: H_k is the observation model which maps the true state space into the observed space; v_k is the observation noise which is assumed to be zero mean Gaussian white noise with covariance R_k.

$$v_k \sim N(0, R_k) \, . \tag{4}$$

The initial state, and the noise vectors at each step $\{x_0, w_1, ..., w_k, v_1 ... v_k\}$ are all assumed to be mutually independent. In order to use the Kalman filter to estimate the internal state of a process, given only a sequence of noisy observations, one must model the process in accordance to the framework of the Kalman filter. This means specifying the matrices F_k, H_k, Q_k, R_k, and sometimes Bk for each time-step k, as described below. The Kalman filter is an efficient recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. In contrast to batch estimation techniques, no history of observations and/or estimates is required. It is unusual in being purely a time domain filter; most filters (for example, a low-pass filter) are formulated in the frequency domain and then transformed back to the time domain for implementation. The state of the filter is represented by two variables:

$\hat{x}_{k/k}$ – the estimate of the state at time k;

$P_{k/k}$ – the error covariance matrix (a measure of the estimated accuracy of the state estimate).

The Kalman filter has two distinct phases: Predict and Update. The predict phase uses the estimate from the previous time step to produce an estimate of the current state. In the update phase, measurement information from the current time step is used to refine the prediction in order to arrive at a new, (hopefully) more accurate, estimate.
Predict Phase:

$$x_k = F_k x_{k-1} + B_k u_k \ \text{(Predicted state)}, \tag{5}$$

$$P_{k/k-1} = F_k P_{k-1/k-1} F_k^T + Q_k \ \text{(Predicted estimate covariance)}. \tag{6}$$

Update Phase:

$$\hat{y}_k = z_k - H_k \hat{x}_{k/k-1} \text{ (Innovation or measurement residual)}, \quad (7)$$

$$S_k = H_k P_{k/k-1} H_k^T R_k \text{ (Innovation (or residual) covariance)}, \quad (8)$$

$$K_k = P_{k/k-1} H_k^T S_k^{-1} \text{ (Optimal Kalman gain)}, \quad (9)$$

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k \hat{y}_k \text{ (Updated state estimate)}, \quad (10)$$

$$P_{k/k} = (I - K_k H_k) P_{k/k-1} \text{ (Updated estimate covariance)}. \quad (11)$$

In the case of the ANN studied here, the sigmoid function was used, as the activation function of each neuron. Because of this, the values of the data variables in the model must be normalized onto range [0.1] before applying the ANN methodology. This problem was solved through the following scaling:

$$V_b^* = \frac{V_b - V_{\min,b}}{V_{\max,b} - V_{\min,b}}, \quad (12)$$

where: V_b are the values of the data variables; $V*_b$ is the scaled value of the variable; $V_{\min,b}$ is the minimum value of variable V_b minus 15%; $V_{\max,b}$ is the maximum value of variable V_b plus 15%.

Hence the scaled series are in the range [0.1]. This scale has the advantage of mapping the desired range of a variable to the full working range of the network input and moreover, the scaled series lies in the central zone of the sigmoid function, where the function is approximately linear. Therefore, during the validation model which is described next, the problem of the output signal saturation that can sometimes be encountered in ANN applications is avoided.

With the use of the Bootstrap method 120 time series of residuals are generated, and consequently to every real value correspond 120 residuals which are randomly distributed around it. The application of the Bootstrap technique is through a special menu called Bootstrap menu. Thus, the Bootstrap method is activated by using as input data of a time series determined by the user. The application of this technique is being realized through sampling with reset, and a number of times series is generated whose number is also determined by the user. The menu is connected internally to a Visual Basic for Applications (VBA) code that implements the method by using the RAND function and by calculating for every real value of the time series of the residuals. This application may determine the number of the bootstrap time series generated by the initial time series (Fig. 2).

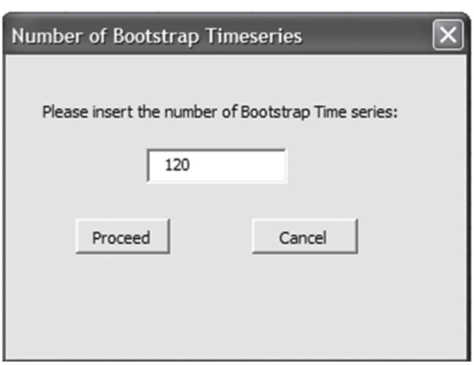

Fig. 2. Determination of Bootstrap time series

Then by using the Insertion sort (Knuth 1998) we estimate the 95% (C.I.) of the

120 generated residuals, and thus we estimated the Upper and Lower Confidence Limits of the 95% (C.I.) of the predicted values. The insertion technique sorts each series by repeatedly taking the next item and inserting it into the final data structure in its proper order with respect to items already inserted.

An example of the code used in order to implement the insertion technique is shown in the following example:

```
Module InsertionSort
  Sub InsertionSort(ByRef a() As Integer)
    Dim i As Integer
    For i = 0 To a.Length - 1
      insert a(i) into sorted sublist
   Next
  End Sub
  test main
End Module
```

Two new time series are created, one of the Upper Confidence Limit (UCL) and the other of the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the predicted prices. Consequently, we use the initial ANN for the calculation of twenty new values of the stock price of Alpha Bank, by using as an input the closing prices of EFG, and also by using an ANN having as input the upper and lower values of the residuals that were calculated by using Bootstrap, we calculate and the new expected upper and lower limits of the forecasted prices, given by the initial ANN.

The results of the methodology are presented in Fig. 3. In this figure we present the observed and the predicted prices of the stock prices of Alpha Bank, the Upper Con-

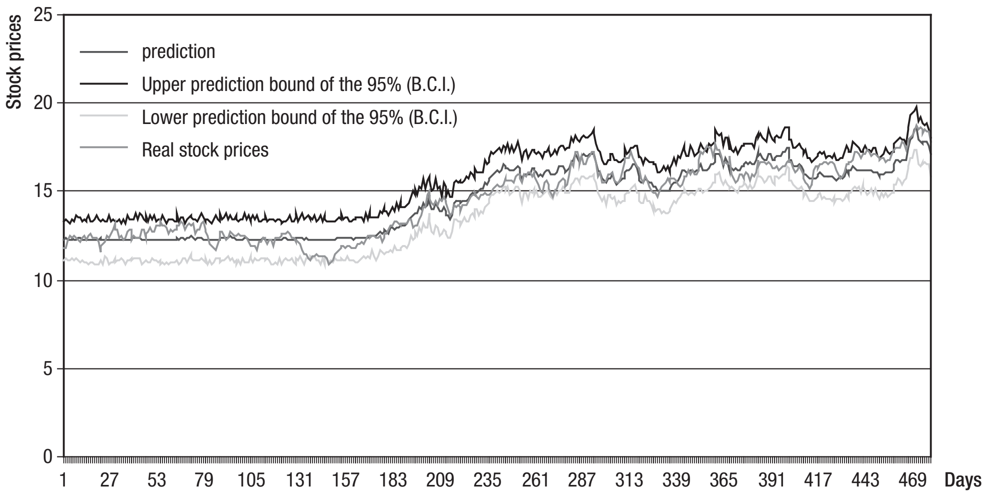

Fig. 3. The observed and the predicted prices of Alpha Bank stock, the Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the predicted pricesTable 1 presents the forecasted prices, the Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the forecasted prices for the last 20 observations of the sample

fidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the predicted prices.

Table 1 presents the forecasted prices, the Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the forecasted prices for the last 20 observations of the sample.

Figure 4 depicts the forecasted prices and the Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the forecasted prices for the last twenty observations of the sample.

Table 1. Forecasted prices Alpha Bank stock, Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL) of the (1-α)*100% (C.I) of the forecasted prices for the last twenty observations of our sample

Observed prices	Forecasted prices	Upper Confidence Limit of the 95% (C.I.) of the forecasted prices	Lower Confidence Limit of the 95% (C.I.) of the forecasted prices
17.93	17.315485	18.42955947	16.09441543
17.89	17.50035477	18.60822296	16.27662981
17.96	17.57427025	18.67965317	16.34950793
18.11	17.18260002	18.30110979	15.96350431
17.86	17.12118912	18.24173307	15.9030273
17.87	16.95606422	18.08198738	15.74048936
17.79	17.0229435	18.14670765	15.80630672
17.86	17.0229435	18.14670765	15.80630672
17.63	16.94869041	18.07484949	15.73323393
17.61	16.91200066	18.03932714	15.69713652
18.03	16.95606422	18.08198738	15.74048936
18.14	17.3791275	18.49106801	16.15713298
17.99	17.18260002	18.30110979	15.96350431
17.84	16.76817131	17.89993477	15.55569184
17.74	16.80368614	17.93437803	15.59060836
17.53	16.5951004	17.73177969	15.38562953
17.66	16.73997498	17.872576	15.52797508
17.66	16.73997498	17.872576	15.52797508
17.91	17.12118912	18.24173307	15.9030273
17.66	16.84669304	17.97606468	15.63289917

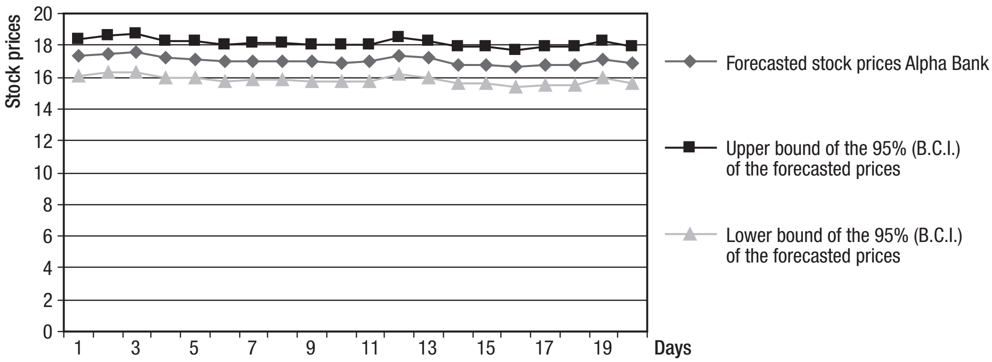

Fig. 4. Observed – Forecasted prices of Alpha Bank stock prices, the upper and lower bound of the 95% (C.I.) of the forecasted prices for the 20 days since 1/12/2005 and the period after

As it becomes evident by the figure the observed and the forecasted prices are bounded by the confidence limits, giving us an indication for the accuracy of the methodology. The following section presents the quantitative evaluation of the forecasting accuracy of the particular methodology.

7. Evaluation of forecasting accuracy of the forecasted prices

The validity of output from ANNs model was tested with the application of different criteria: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Normalized Objective Function (NOF) and Theil's U – Statistic. The parameters RMSE, MAPE and NOF have to be as close to 0.0 as possible for the forecast to be considered satisfactory. However, when the parameter NOF is less than 1.0, then the theoretical method is reliable and can be used with sufficient accuracy (Hession *et al.* 1994; Kornecki, Sabbagh 1999; Tsihrintzis *et al.* 1998). The Theil's U – Statistic must be less than one.

According to the results we calculate the following evaluation criteria of accuracy of forecasting; RMSE = 0.8192, MAPE = 4.4819%, NOF = 0.048087 and Theil's U – Statistic = 0.048082.

The NOF is the ratio of the RMSE to the overall mean $<\hat{y}_t>$ of the forecasted by the model data (Tsihrintzis *et al.* 1998), defined as:

$$\text{NOF} = \frac{\text{RMSE}}{<\hat{y}_t>}, \tag{13}$$

where:

$$<\hat{y}_t> = \frac{1}{M}\sum_{1}^{M}\hat{y}_t \tag{14}$$

is the average value of the model output data.

The Theil's U – Statistic defined as:

$$U = \frac{\text{RMSE}}{\sqrt{\frac{\sum_{t=1}^{M} \hat{y}_t^2}{M}}}, \tag{15}$$

where: $\hat{y}_t$ the forecasted prices and M the number of the forecasted prices.

8. Evaluation of forecasting accuracy of the (1-a)*100% Confidence Intervals of the Forecasted prices

For the Evaluation of forecasting accuracy of the (1-a)*100% Confidence Intervals of the Forecasted prices, a statistical test as follows is introduced;

We define the following distances:
| Observed price – Forecasted price |, | Forecasted price – UCL |, | Forecasted price – LCL | for all the Forecasted prices.

We also define the min {| Forecasted price – UCL |, | Forecasted price – LCL |} for all the Forecasted prices.

If the Probability,
P (|Observed price – Forecasted price | ≤ min { Forecasted price – UCL |, | Forecasted price – LCL |} ≥ 1-a, for all the forecasted prices then we can agree that (1–a)*100% Confidence Intervals of the forecasted prices give a satisfactory forecast.

The absolute value of the differences (Observed – Forecasted), (Forecasted – UCL), (Forecasted – LCL) for all the Forecasted prices are given in Table 2.

Table 2. The absolute value of the differences (Observed – Forecasted), (Forecasted – UCL), (Forecasted – LCL) for all the Forecasted prices

Absolute (Observed – Forecasted)	Absolute (For – UCL)	Absolute (For – LCL)
0.614515	1.1140745	1.22106957
0.389645	1.1078682	1.22372496
0.38573	1.1053829	1.22476232
0.9274	1.1185098	1.21909571
0.738811	1.120544	1.21816182
0.913936	1.1259232	1.21557486
0.767056	1.1237642	1.21663678
0.837056	1.1237642	1.21663678
0.68131	1.1261591	1.21545648

End of Table 2

Absolute (Observed – Forecasted)	Absolute (For – UCL)	Absolute (For – LCL)
0.697999	1.1273265	1.21486414
1.073936	1.1259232	1.21557486
0.760873	1.1119405	1.22199452
0.8074	1.1185098	1.21909571
1.071829	1.1317635	1.21247947
0.936314	1.1306919	1.21307778
0.9349	1.1366793	1.20947087
0.920025	1.132601	1.2119999
0.920025	1.132601	1.2119999
0.788811	1.120544	1.21816182
0.813307	1.1293716	1.21379387

Consequently, given that the probability;
P (| Observed price – Forecasted price | ≤ min { | Forecasted price – UCL |, | Forecasted price – LCL | } ≥ 0.95 for all the forecasted prices, then we may argue that the (1-a)*100%Confidence Intervals of the forecasted prices may give us a satisfactory forecast.

9. Conclusion – Discussion

This is the first time that the hybrid method described above is used in Finance. The particular methodology is combinational, since the Bootstrap method and ANNs are used for the determination of the (1-α)*100 % (C. I.). The method was used to estimate the C.I. involving the predicted values of stock prices. We used the aforementioned Hybrid method for first time in the field of Finance. The method is completed in four steps. The main objective of this survey was to estimate the C.I. of the predicted values regarding the initial time series and its main accomplishment was to amplify the validity of the (1-α)*100% Confidence Interval of the forecasted prices. We used different forecasting criteria like RMSE, MAPE, NOF and Theil's U – Statistic. In order to test the forecasting ability of the particular methodology, based on the results we calculated the following evaluation criteria of accuracy of forecasting RMSE = 0.8192, MAPE = 4.4819%, NOF = 0.048087 and Theil's U – Statistic = 0.048082, that all confirm a satisfactory forecast.

In the future, this method could be further developed with the use of another programming language in order to create a stand alone software toolbox for the prediction of stock prices.

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VERTYBINIŲ POPIERIŲ KAINŲ PROGNOZAVIMAS HIBRIDINIU METODU: *ALPHA BANK* PAVYZDYS

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Santrauka

Šio tyrimo tikslas – nustatyti pasikliautinuosius intervalus (*Confidence Intervals*, C. I.) prognozuojamam periodui taikant hibridinį metodą (*Hybrid*). Pateikta metodika yra sudėtinga, todėl autoriai jos taikymą suskirstė į kelias fazes. Pradžioje buvo taikyti metodai, pagrįsti dirbtiniais neuroniniais tinklais, kurių pritaikymas leido atlikti pasikliautinųjų intervalų ribų prognozes. Vėliau autoriai taikė *Bootstrap* metodą.

Siekiant nustatyti viršutines ir apatines pasikliautinųjų intervalų ribas, taikant dirbtinių neuroninių tinklų metodą, buvo remtasi į objektą orientuotu programavimu. Empirinei analizei atlikti kasdien autoriai naudojo *Alpha Bank* pateikiamus duomenis. Analizuojamas laikotarpis apėmė 2004-01-28–2005-11-30.

Reikšminiai žodžiai: dirbtiniai neuroniniai tinklai, pasikliautinieji intervalai, Bootstraop metodas, programavimas, fondų birža.

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